42172 AT1: Forest Fire Spread Prediction

PART: 2

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LINK TO SOLUTION NOTEBOOK:
[Google Colab]
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Summary or Executive Summary

Purpose

Reevaluates the recommendation of previous literature by comparing data mining model solutions to predict the spread of forest fires in Montesinho park in Norther Portugal.

Techniques

Analyses the regression task using support vector machine (SVM) and deep neural networks and compares the effect of both z-score and min-max normalization on each model.

Findings

This report found that generally, a z-score normalized deep neural network performs best when predicting the area spread of forest fires. Neither normalization technique significantly affects the results of the SVM regressor. Although the min-max normalized neural network did not make the most accurate prediction, it still outperformed both SVM configurations.

Conclusion

Forest fire prediction is directly related to the preparedness of first responders and thus requires the highest accuracy. The results of this paper contradict the findings in previous works that recommended a z-score SVM regressor.

Recommendation

Authorities should generally use a z-score normalized neural network as they are more scalable and the absence of input bounds allows it to be implemented into real-time systems with high accuracy.

Introduction

What was the problem and its context? (including data sources)

Cortez and Morais (2007) produced a work that determined that a support vector machine (SVM) regressor is the most accurate data mining model in predicting the scale of forest fires in Montesinho park located in Northern Portugal by using meteorological data. The study compared SVM, random forests, decision trees, and a shallow neural network.

Why was it a problem?

The evaluation of only a shallow neural network in the previous literature is such the final recommendation could be argued as unsatisfactory. As the topic of natural disaster prevention bears much consequence. It is imperative that the most accurate model in these systems are chosen for the task.

Why was the project necessary and how was the problem solved?

Forest fire prediction is inherently a mission critical system that directly influences the preparedness of first responders. Hence, this report extends on the work of (Cortez & Morais, 2007) to determine if deep neural networks are able to more accurately predict the spread of forest fires. The same dataset is used as in previous literature and both z-score and min-max normalization are used on all input features to train 2 separate configurations of SVM regressor and deep neural network respectively. All 4 models are evaluated against a mean square error (MSE) and a final recommendation is made.

Report Body

Methods/AI techniques used

Regression Models

What are regression models?

Regression models are stochastic methods of predicting a continuous target variable by learning the correlations and trends in a training set.

How are regression models evaluated?

Comparatively to classification problems, regression models are not limited to making predictions between 0 and 1. Hence, metrics such as accuracy, precision, recall, etc are not useful in evaluating the accuracy of regression models. Rather, regression models are evaluated based on the error from the predicted value to the observed value. Typical examples of regression metrics are mean square error (MSE), root mean square error (RMSE), and mean absolute error (MEA).

How do they relate to the problem context?

For this work, the selected models attempt to predict the spread of forest fires in the Montesinho park located in northern Portugal.

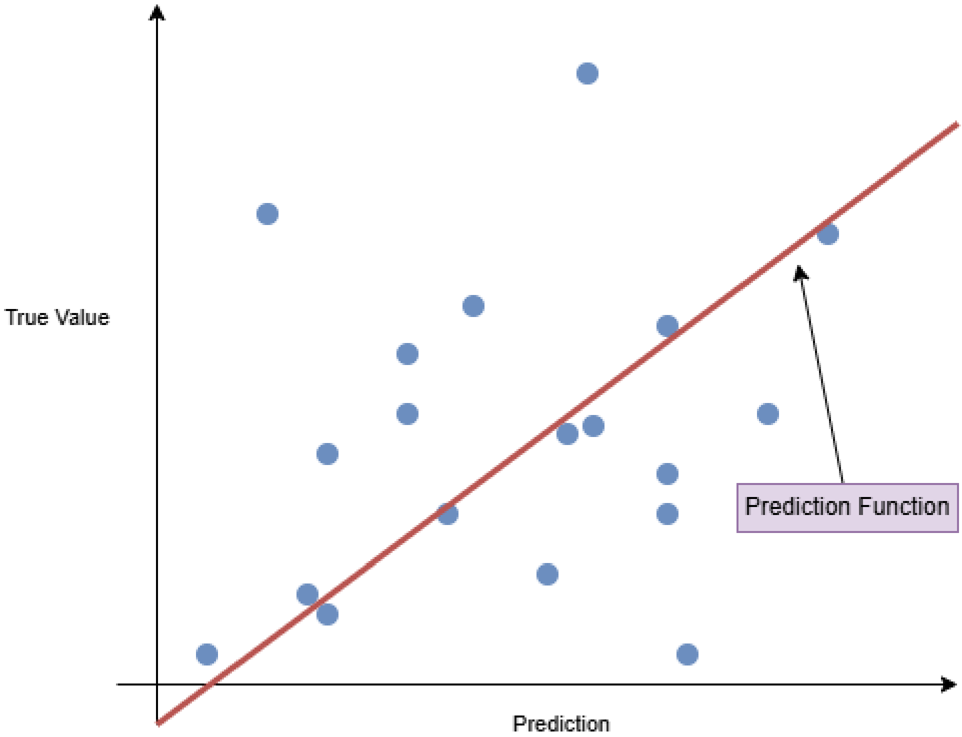


Figure 1: Regression

Neural Network

Description of the technique

Forward pass

In the forward pass stage, the dot product of each input and their respective weights are parsed into each neuron in the hidden layers. An activation function is used on the aggregated dot product to form some non-linear function. This process continues for each hidden layer until a final output has been produced.

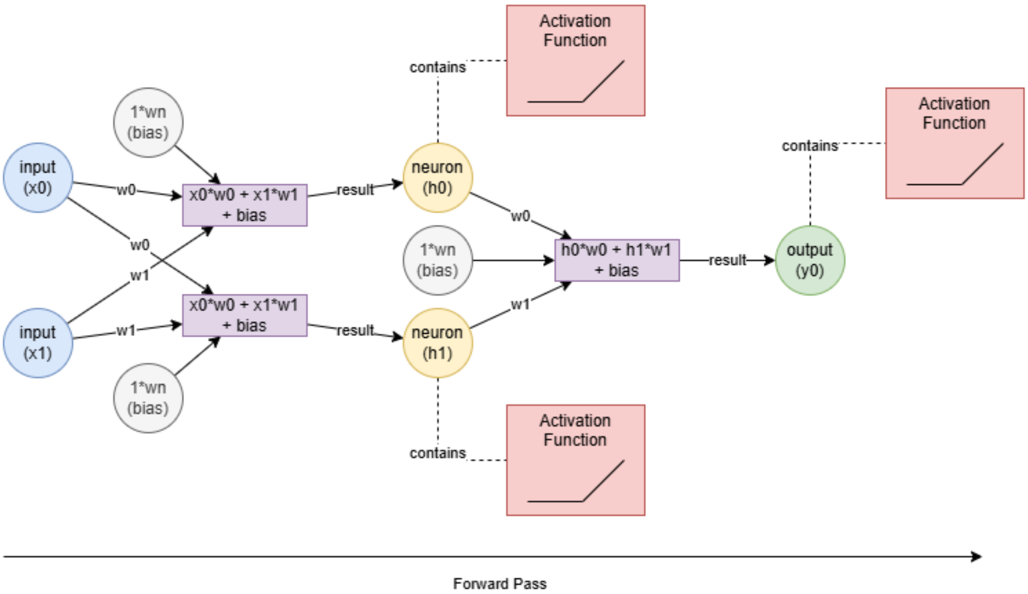


Figure 2: Forward Pass

Back propagation

In the back propagation stage, the weights (w) of each neuron that is composed of an activation function and a dot product $(w_0 h_0 + w_1 h_1 + bias)$ is increased or decreased by a learning rate such that the result of the loss function (error) approaches the minima. This process starts from the end of the neural network and propagates backwards towards the input layer.

Loss function: Used to calculate how accurate the predicted output is compared to the true value. This work uses mean square error as the primary loss function for the configured neural network.

$$\text{Let each instance of inputs} = i$$
$$\text{Let predicted output at each instance} = y_i$$
$$\text{Let true value} = t$$
$$\text{Error at any instance} = (y_i - t_i)^2$$
$$\text{Mean Square Error } (MSE) = \frac{\sum_{i=0}^{n}(y_i - t_i)^2}{n}$$

Gradient Descent: To find the minima of the loss function, the neural network iteratively increases or decreases the weights in each neuron by the learning rate such that the gradient of the loss function approaches zero.

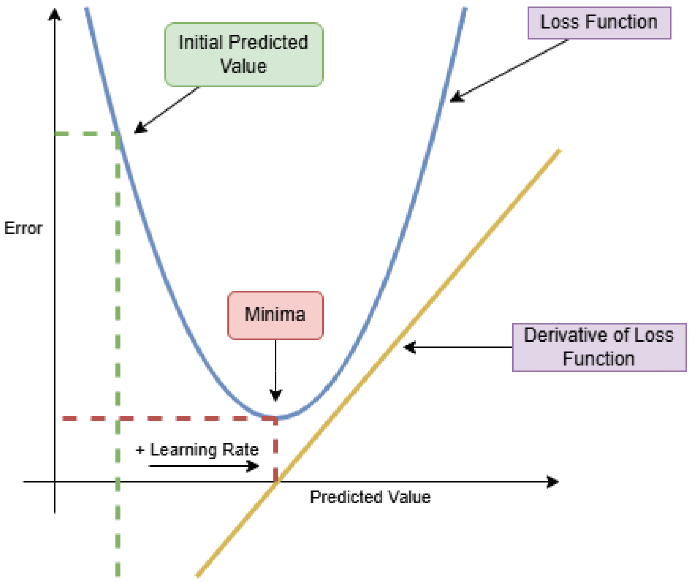


Figure 3: Back propagation

Why was this algorithm chosen?

In the work of Cortez and Morais (2007), a single hidden layer neural network was used to predict the area spread of forest fires in the Montesinho park. In contrast, this report evaluates a neural network configuration using multiple hidden layers. Additionally, neural networks are a method of parametric modelling that performs well in determining non-linear patterns in data.

Support Vector Regressor

Description of the technique

Unlike the support vector machine (SVM) classifier, the support vector regressor produces a prediction function that simultaneously minimizes the error rate (ξ) from the decision boundary and maximizes the number of data points within the decision boundary. The resulting hyperplane function is used to make predictions for subsequent data points.

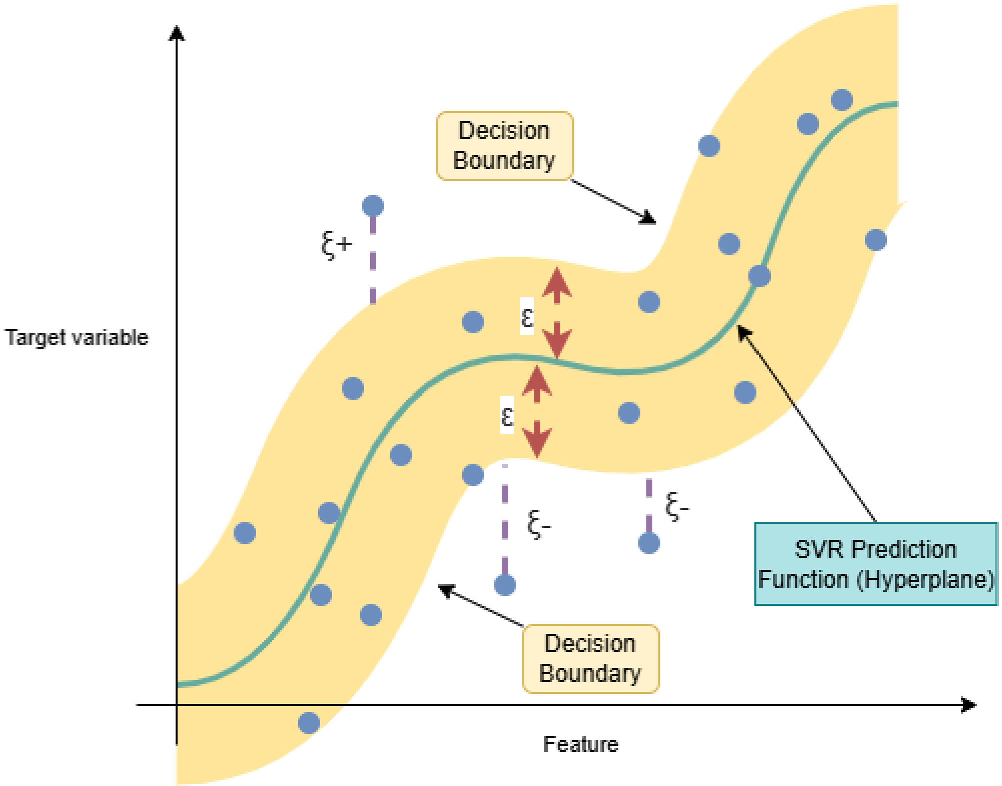


Figure 4: SVM regressor

Why was this algorithm chosen?

SVM was the recommended model in the work of Cortez and Morais (2007). Hence, it was selected to be evaluated against neural networks with multiple hidden layers. Although SVM is typically associated with classification modelling, it is still able to learn and form a non-linear prediction function.

Implementation of AI techniques

Programming Environment

Variable	Description
CPU	Intel(R) Core(TM) i7-4600M CPU @ 2.90GHz 2.89 GHz
RAM	8.00 GB
Python	Version 3.12.4 Programming language for model implementation.
Anaconda	Version 24.5.0 Jupyter notebooks interface for local testing environment.
Google Colab	Uniform external testing environment for jupyter notebooks.

Libraries

Package	Usage
Pandas	Data handling interface for slicing and transforming forest fire data.
NumPy	Array transformations and mathematical operations.
MatplotLib	Data visualizations.
Scikit-learn	Data normalization/standardization, SVM regression implementation, and mean square error metrics evaluation.
Tensorflow	Neural network regression implementation.

Data Source

The data for this report was acquired from the work of Cortez and Morais (2007) that includes 517 rows and 13 columns of meteorological data and features from the fire weather index (FWI).

Data Dictionary

Feature	Data Type	Description
X	Interval	x-axis spatial coordinate within the Montesinho park map: 1 to 9
Y	Interval	y-axis spatial coordinate within the Montesinho park map: 2 to 9
month	Ordinal	month of the year: "jan" to "dec"
day	Ordinal	day of the week: "mon" to "sun"

FFMC	Ratio	FFMC index from the FWI system: 18.7 to 96.20
DMC	Ratio	DMC index from the FWI system: 1.1 to 291.3
DC	Ratio	DC index from the FWI system: 7.9 to 860.6
ISI	Ratio	ISI index from the FWI system: 0.0 to 56.10
temp	Interval	temperature in Celsius degrees: 2.2 to 33.30
RH	Ratio	relative humidity in %: 15.0 to 100
wind	Ratio	wind speed in km/h: 0.40 to 9.40
rain	Ratio	outside rain in mm/m2 : 0.0 to 6.4
area	Ratio	the burned area of the forest (in ha): 0.00 to 1090.84

Data Exploration

Time

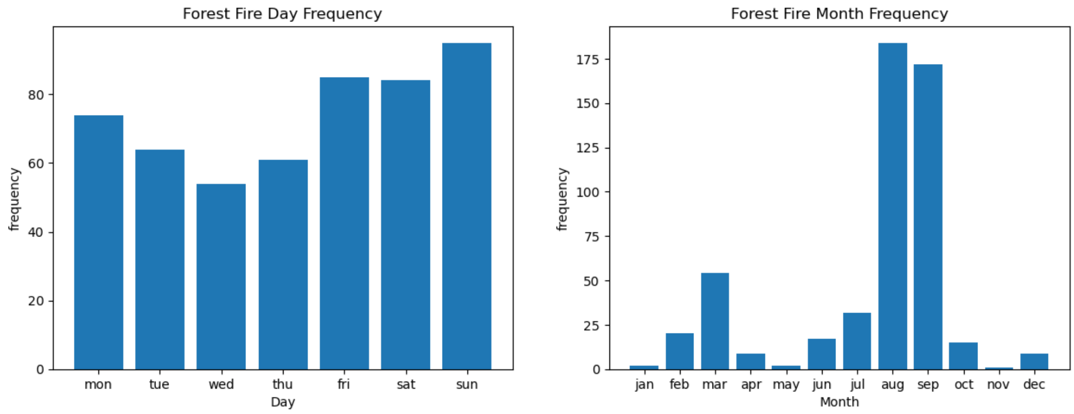
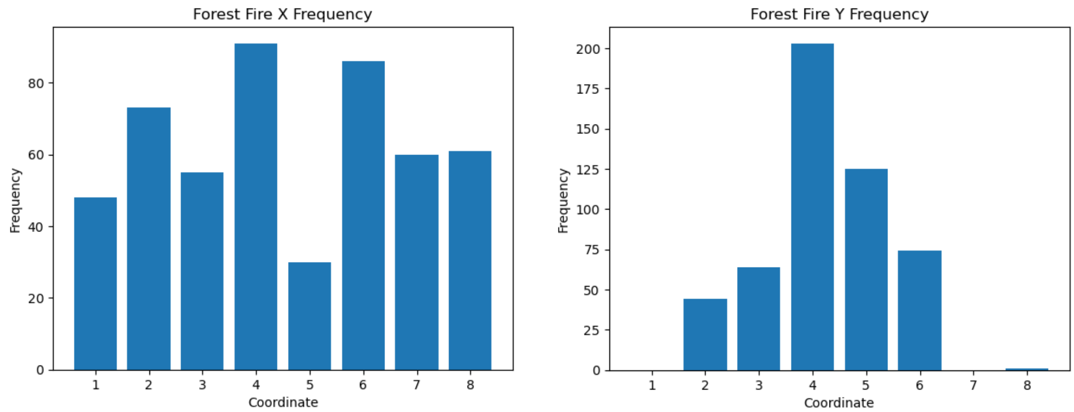


Figure 5: Forest fire outbreaks appear to be most frequent from Friday to Sunday and during the months August to September.

Location



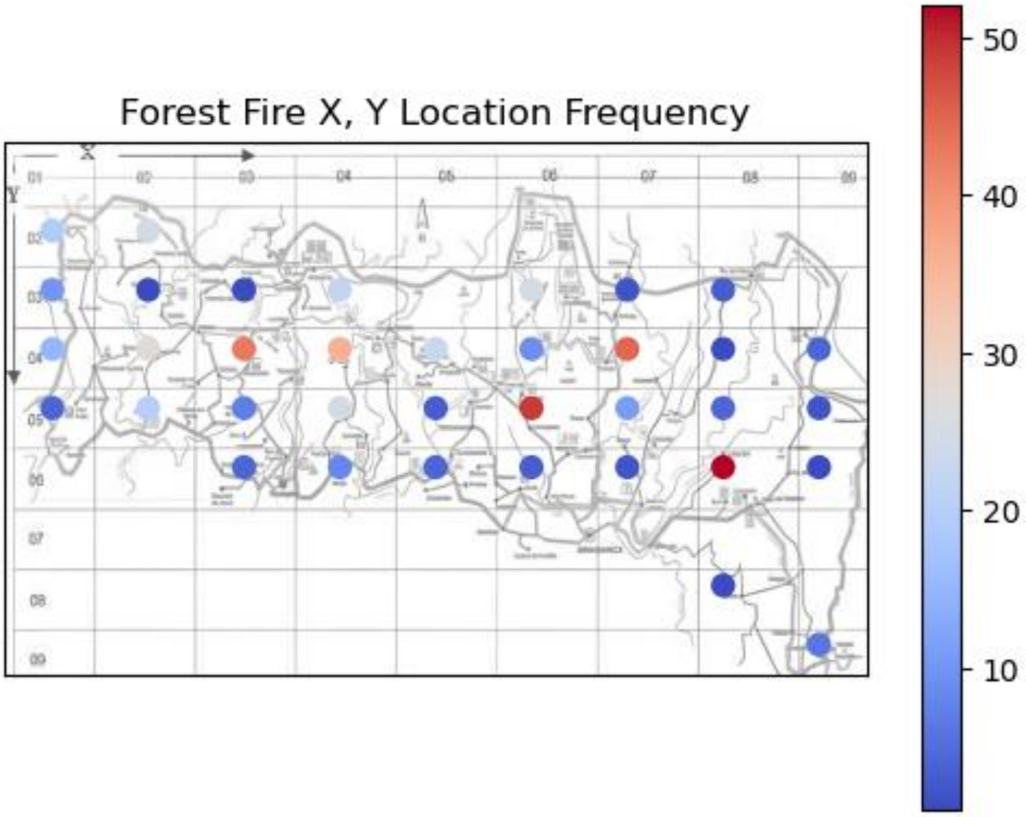


Figure 6: The frequency of forest fires is shown to appear on the central right and central left areas in Montesinho park.

FWI System

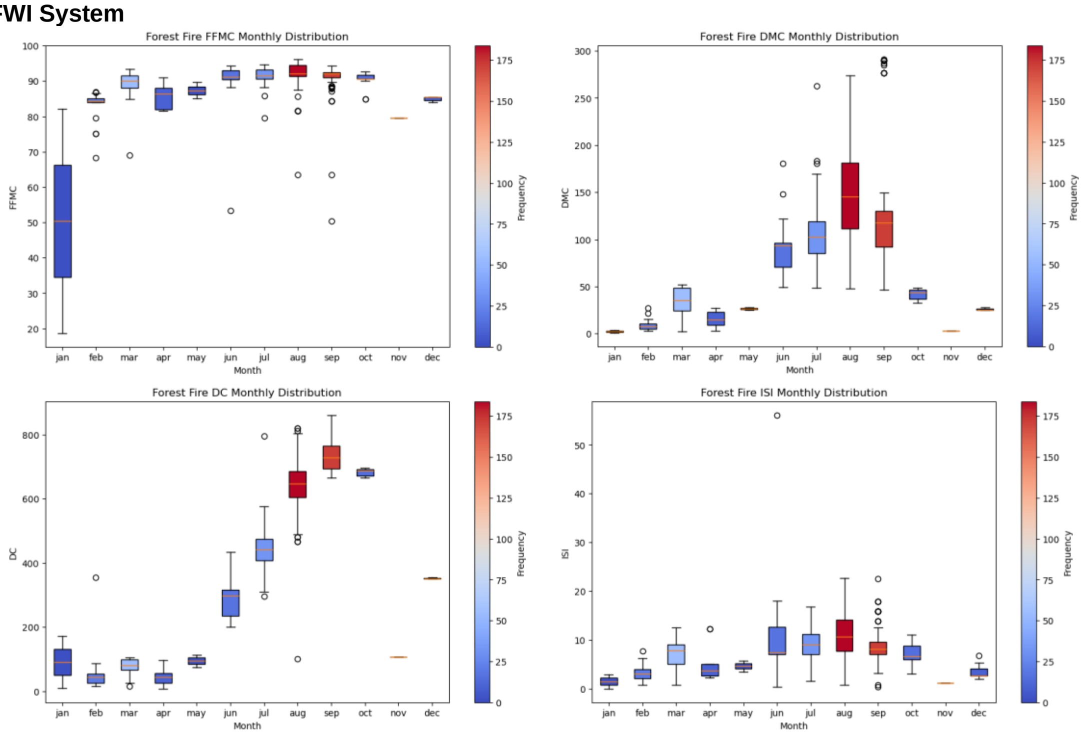


Figure 7: The FWI feature at each month appears somewhat correlated to forest fire frequency.

Weather

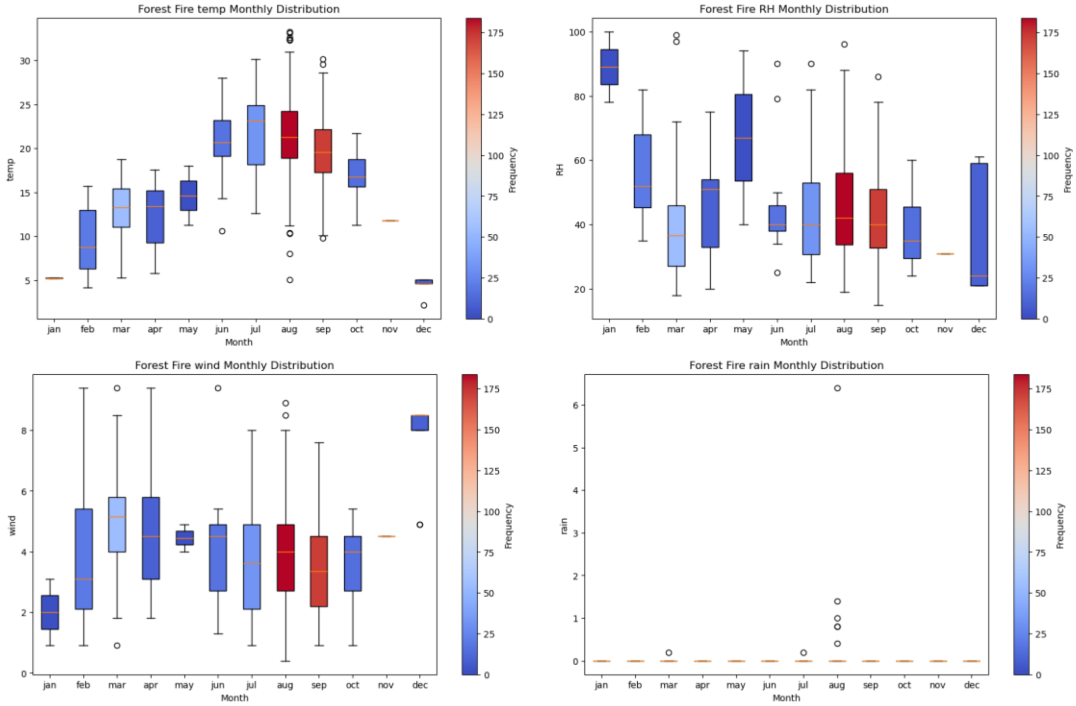


Figure 8: Temperature during the summer-spring months is shown to be higher and thusly have a higher frequency of forest fires. Interestingly, wind speeds do not appear to be closely correlated to time of year nor the frequency of forest fires. Additionally, rain is infrequent in Montesinho park.

Area

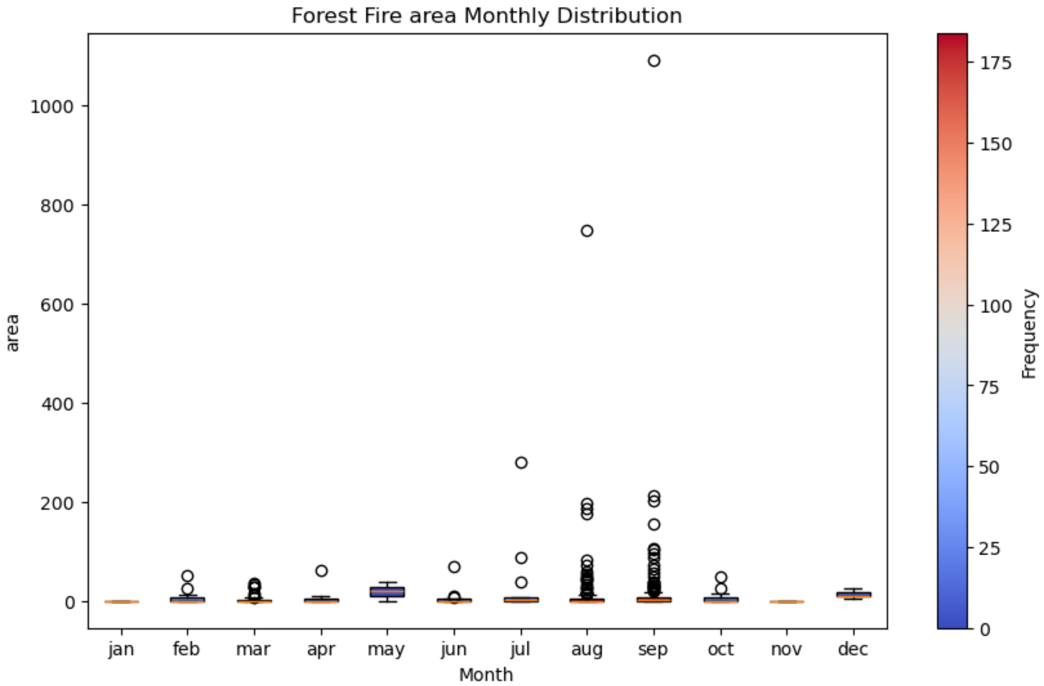


Figure 9: Burned area is composed of a wide range (0.00 to 1090.84 ha) with most instances distributed at zero for all months.

Data Preprocessing

Feature Scaling

Feature	Transformation
Area:	As seen in the data exploration section, the "Area" feature shows a wide range where many data points are distributed around zero. As this study employs the use of neural networks, wide target variable ranges may slow down the learning rate of the model. Hence a $\log(x+1)$ transform was applied to the target variable to reduce its range.

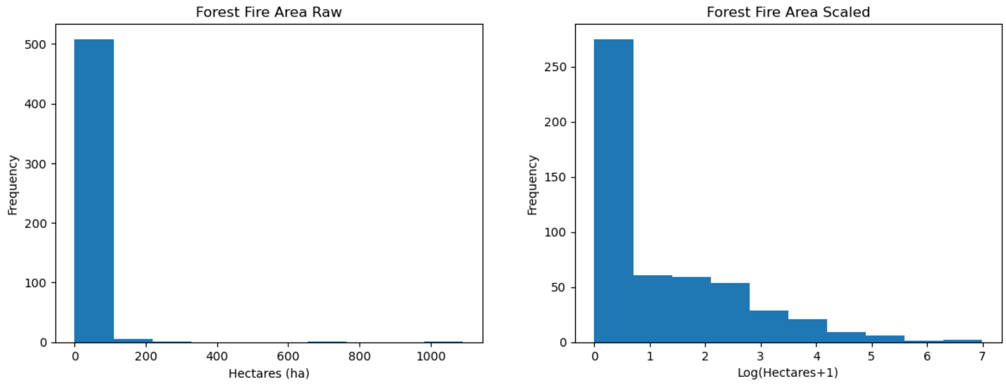


Figure 10: Comparison of pre and post-scaled forest fire area data.

Normalizations

For this report, normalization/standardizations were performed on all input features such that the ranges between each feature are not disproportionate to one another. This is significant as for SVM, variable feature ranges could influence the determining hyperplane and decision boundaries. While for neural networks, inconsistent feature ranges may cause oscillations or increase the number of iterations required to learn from the data.

Technique	Description/Justification
Z-Score:	Transforms the feature such that standard deviation is equal to 1 and the median is set to 0. This method is useful for models that may receive new instances that fall outside the maximum and minimum ranges of the existing dataset. $x: feature\ instance$ $\bar{x}: feature\ mean$ $\sigma: standard\ deviation$ $x' = \frac{x-\bar{x}}{\sigma}$
Min-Max:	This technique distributes the feature between 0 and 1. It is useful in ensuring that all features have the same weight during model training. However, it is not designed to be used for instances where inputs fall outside the existing minimum-maximum feature range. $x: feature\ instance$ $x' = \frac{x-\min(x)}{\max(x)-\min(x)}$

Correlations

The correlations matrix shows that excluding the month feature, no other feature appears particularly indicative of predicting the target variable (area) for both pearson and spearman correlations. Hence for this report, no features were removed nor created for model training.

```
zscore_ff.corr(method="pearson"
)["area"]
X          0.061995
Y          0.038838
month      0.114280
day        0.000208
FFMC       0.046799
DMC        0.067153
DC         0.066360
ISI       -0.010347
temp       0.053487
RH        -0.053662
wind       0.066973
```

```
zscore_ff.corr(method="spearman"
)["area"]
X          0.060499
Y          0.046018
month      0.117681
day       -0.016799
FFMC       0.025300
DMC        0.071920
DC         0.061633
ISI        0.012496
temp       0.078696
RH        -0.024221
wind       0.053196
```

```
rain       0.023311
area       1.000000
Name: area, dtype: float64
minmax_ff.corr(method="pearson"
)["area"]
X          0.061995
Y          0.038838
month      0.114280
day        0.000208
FFMC       0.046799
DMC        0.067153
DC         0.066360
ISI       -0.010347
temp       0.053487
RH        -0.053662
wind       0.066973
rain       0.023311
area       1.000000
Name: area, dtype: float64
```

```
rain      -0.064073
area       1.000000
Name: area, dtype: float64
minmax_ff.corr(method="spearman"
)["area"]
X          0.060499
Y          0.046018
month      0.117681
day       -0.016799
FFMC       0.025300
DMC        0.071920
DC         0.061633
ISI        0.012496
temp       0.078696
RH        -0.024221
wind       0.053196
rain      -0.064073
area       1.000000
Name: area, dtype: float64
```

Experiments

Normalization

This work compares the effect of normalization methods on both SVM and neural network models as forest fire prediction is a mission critical system, it is important to select the model that produces the most accurate results. As outlined in the data preprocessing section, z-score and min-max normalization methods were selected for this study. Additionally, variations in feature scales/ranges may affect the accuracy of each model due to distances between data points.

Support Vector Regressor

Parameter	Configuration	Justification
Kernel	Radial Basis Function	RBF is a popular kernel for lower dimensional data and is the same method used by Cortez and Morais (2007) on the same dataset.
Epsilon	1	Multiple epsilon values were tested between the ranges from the default 0.1 to 2. Ultimately, the values producing the best performance were between 0.8 and 1.5. This study settled on the value of 1.

Neural Network

Parameter	Configuration			Justification
Hidden layers	3			Configurations of hidden layers between 1 and 4 were evaluated. This work prioritised increasing the depth of the network before depth and found 3 hidden layers generally produced lower MSE scores compared to alternate configurations where the model would be over or underfitted.
Neurons	Layer x_i h_0 h_1 h_2 y_i	Z-score 12 256 128 32 1	Min-Max 12 32 16 8 1	As mentioned previously, model depth was prioritised over breadth. Neuron selection began from 100 neurons at each hidden layer. Based on the resulting MSE score, the number of neurons at each hidden layer were manually configured until an acceptable error was produced.
Activation Function	Rectified Linear Unit			The RELU activation function was adopted as opposed to sigmoid due to the nature of the regression problem.
Epochs	10			Epoch selection began from 100 as outlined in previous literature (Cortez & Morais, 2007) and were manually adjusted until an acceptable MSE was produced.

Batch Size	8	Manually selected in exponents of 2 to limit over/underfitting.
Loss Function	Mean Square Error	Same as the regression metric that this study evaluates both models on.
Optimizer	Adam	Efficient method for adjusting the learning rate of the neural network that is a combination of gradient descent and RMSProp optimizer. (prakharr0y, 2024)

K-Fold Cross-Validation

The k-fold cross-validation method was selected for this work as opposed to a single train-test split validation for increased robustness in model evaluations.

Parameter	Configuration	Justification
n splits	5	Each split iteration tests against 20% of the dataset. This configuration is common among test splitting and attempts to retain the representativeness of the dataset in each split.
Shuffle	True	Randomizes the dataset before splitting. This is useful in the case that the dataset is initially ordered.

Model Evaluations

Mean Square Error

MSE was chosen as the primary metric of evaluation for simple interpretability and the direct relation to the loss function in the neural network model.

Results

$\boldsymbol{Model}$	$\mathbf{MSE}: \mathbf{log}\ (\boldsymbol{x}+\mathbf{1})$	$\boldsymbol{Error}: \boldsymbol{Hectares}\ (\boldsymbol{ha})$
Z-score NN	1.788	2.809
Z-score SVM	1.959	3.054
Minmax NN	1.897	2.965
Minmax SVM	1.944	3.032

Findings

In both normalization cases the neural network performed better than the SVM regressor. Additionally, the z-score neural network appears to have significantly increased the accuracy of predicted results comparatively to every other model. Notably, neither normalization technique appears to produce any significant difference in model accuracy for SVM models.

Comparisons of different AI techniques

Support Vector Regressor

Advantages

- Robust to small datasets
- Optimal margin

Disadvantages

- Scalability
- Difficulty handling high-dimensional data

The robustness of the SVM regressor was such that MSE did not significantly change despite the differing normalization transforms on the dataset. Although the epsilon parameter was tested throughout multiple ranges, the model performed well in identifying a similar optimal margin with an epsilon range between 0.8 to 1.5.

The Montesinho park forest fire dataset is relatively small such that the model was able to make reasonably accurate predictions. However, increasing the number or rows to a greater time series range or adding columns/dimensions may introduce complexity that is difficult for this method to handle.

Neural Network

Advantages

- High complexity handling
- Scalability

Disadvantages

- Data dependency
- Overfitting

This report showed that deep neural networks were able to capture the complexity in forest fire data. In the earlier parameter configuration stages, it was found that incorrectly tuning these parameters would cause overfitting or underfitting.

Despite the limited size of the Montesinho park forest fire dataset, the neural network model was able to make more accurate area spread predictions compared to both minmax and z-score normalized configurations of SVM. It was found that the feature scaling of input variables has a significant impact on model accuracy where z-score normalization produced more accurate results.

Conclusions and Recommendations

Conclusion

The results of this study show that for both normalization methods, deep neural networks can more accurately predict the spread of forest fires in Montesinho park compared to SVM regressors. In the case of mission critical systems, making accurate predictions of the potential harms are imperative for first responders. Previous work by Cortez and Morais (2007) found that an SVM regressor were able to predict the scale of forest fires more accurately than a neural network with a single hidden layer. This report expands on previous literature to identify a solution that produces more accurate solutions in a state of emergency. Further work into this topic would enable authorities to appropriately respond to outbreaks and could be scaled to different geographies and meteorological conditions.

Recommendation

When comparing each configuration of neural networks and SVM regressors, it is recommended that authorities choose some configuration of deep neural network. As shown in the model evaluations, deep neural networks outperformed SVM regressors across a robust k-fold cross-validation method. This is justified as the accuracy of mission critical systems directly influence the preparedness of first responders. When selecting any given deep learning method, a z-score normalized deep neural network generally produces more accurate results. As z-score normalization is not bound by minimum and maximum ranges, this configuration can be applied to real-time predictions systems.

List of References

Cortez, P., & Morais, A. d. J. R. (2007). A data mining approach to predict forest fires using meteorological data.

prakharr0y. (2024, 20 Mar, 2024). *What is Adam Optimizer?* Geeks for Geeks. Retrieved 28 Sep, 2024 from https://www.geeksforgeeks.org/adam-optimizer/

Individual reflection

Planning
Read through the reference material.
Identified the hyperparameters used in previous literature.
This report did not attempt to perfectly mirror the reference literature, but to determine the intuition behind the study and incorporate justifiable actions into this work.
Any intuition that did not appear completely sound was reevaluated or generalized. For example: normalization process in previous literature only considered z-score normalization where this work used both normalization processes in the experimentation.

Learnings
Clarified the process of back propagation and gradient descent
Approached SVM from a new perspective where instead of classification, the model was used for a regression task.

Challenges
Encountered difficulty tuning the hyperparameters for each configuration of neural network.
Perhaps performing some method of cross-validation to find the optimal configuration of neural network and SVM parameters would be more correct.
The reference material covered some level of depth that is beyond my current knowledge. Hence it was difficult to mirror the exact process that was used and to effectively justify the chosen parameters (e.g. Sequential Minimum Optimization algorithm).

Limitations
The experimentation in previous work was done using the R programming language.
Differing programming environments may have variations in the default parameters and/or implementations of data mining models. Thus, it was difficult to directly mirror the prior case study.

Future
Apply meteorological data for different regions to evaluate the model effectiveness in different geographies.
Vary the size of the dataset to evaluate accuracy for more complex data.
Implement selected models into real-time systems and determine the accuracy of predictions while the system is in production.